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Data Analytics in Fraud Prevention and Detection by Government Internal Supervisory Apparatuses at Ministries/Institutions/Local Governments: A Mixed-Method Study

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ABTRACT
This study investigates differences in internal audit effectiveness and data analytics (DA) usage by the Government's Internal Supervisory Apparatus (GISA) in fraud prevention and detection (FPD). It examines variations in DA usage based on GISA effectiveness and independence, motivations for DA use, application methods, and the effectiveness of DA tools. Using a mixed-method approach, data was collected via questionnaires and interviews. Independent Samples T-Test results indicate significant differences in internal audit effectiveness and DA usage between high and low DA usage groups across the full sample and within ministries/institutions. Significant differences in DA usage are also found based on GISA effectiveness and independence across the full sample and within ministries/institutions, but not within local governments. Key motivations for DA use include improving FPD efficiency, and DA has shown to enhance anomaly detection and audit scope, with Microsoft Excel and Audit Command Language (ACL) as the most used tools. Findings suggest optimized DA use through expanded access, training, and tailored resource.

Keyword: Data Analytics, Fraud Detection, Fraud Prevention, Government Internal Supervisory Apparatus, Internal Audit Effectiveness, Audit Independence.

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1. INTRODUCTION

Fraud and corruption within government sectors, such as ministries, institutions, and local governments, affect both income and expenditures, leading to significant losses, especially in areas like procurement (ACFE, 2020). For example, corruption in healthcare can limit medical supplies, while misallocated infrastructure funds lead to poorly constructed facilities, both harming public welfare. Fraud and corruption also deter investment, lower economic growth, and widen income inequality, making fraud prevention in government essential to sustaining public trust and ensuring resources reach the public effectively.

Transparency International's 2023 report shows a four-point drop in Indonesia's 2022 Corruption Perceptions Index (CPI), the largest decline since 1995, signaling ineffective anti-corruption efforts and limited stakeholder accountability. This decline weakens public trust, discourages investment, and affects economic stability and job creation. Despite government efforts to strengthen anti-corruption measures, persistent issues in enforcement have allowed misallocation of public funds meant for infrastructure and services, ultimately harming public welfare. A Corruption Eradication Committee (KPK) study further identifies weak enforcement and oversight as core challenges, underscoring the need for stronger mechanisms to prevent financial mismanagement.

The Government Internal Supervisory Apparatus (GISA) plays a central role in assessing fraud risk but faces challenges such as limited data access and resource constraints. Unlike external auditors, GISA's access to internal processes and operational data should enable it to detect irregularities more effectively, though these challenges currently hinder optimal performance.

GISA's internal auditor role provides a unique advantage, with direct access to internal data and an understanding of organizational processes that should enhance fraud detection. For instance, GISA's access to procurement records has enabled it to identify irregularities that external auditors might miss. These advantages could be enhanced with additional resources and data analytics tools for earlier fraud detection and better accountability.

The Corruption Eradication Committee (KPK) study (2017) found GISA's role in preventing corruption is limited, often due to organizational hierarchy that restricts independence. Strategies like audits and surprise inspections have limited impact without enforcement, emphasizing the need for more independent and empowered internal oversight to prevent financial misconduct and improve governance.

Data analytics could strengthen GISA's audit function, though limitations in training, data access, and budget impact its use. To address these, GISA could focus on enhanced data analytics training and partnerships for affordable technology solutions, which would improve fraud detection by identifying patterns and anomalies more effectively.

Data analytics facilitates fraud prevention by enabling early anomaly detection, with studies showing organizations using analytics report higher fraud detection rates and quicker recoveries (Banarescu, 2015). Integrating data analytics into GISA's audit functions enables continuous monitoring, reducing response times and increasing detection efficacy.

Previous research offers mixed findings on data analytics in fraud prevention. Studies by Li et al. (2018) and Rakipi et al. (2021) found that analytics improves fraud detection, but Shabani et al. (2022) highlight challenges like data access and regulatory issues. In Indonesia, GISA faces similar barriers, making improvements in data governance and auditor training essential for adapting these insights to the local context.

Given these challenges, this study investigates the role and impact of data analytics within GISA's internal audit functions across government sectors, with a focus on data analytics usage and internal audit effectiveness and independence. Accordingly, the study addresses the following research questions:

a. Are there differences in internal audit effectiveness based on GISA's data analytics usage?
b. Are differences in GISA's data analytics usage associated with internal audit effectiveness in fraud prevention and detection?
c. Are there differences in GISA's data analytics usage based on its independence in fraud prevention?
d. What motivates GISA's choice to use or not use data analytics?
e. How are data analytics tools used by GISA?
f. How effective is GISA's use of data analytics in fraud prevention and detection?

This study offers several contributions. First, this study addresses a research gap by providing evidence on the role of data analytics in fraud prevention and detection through internal audits within the Indonesian government. Second, it compares GISA across ministries, institutions, and local governments, highlighting variations in data analytics usage. Third, it employs a mixed-methods approach, integrating quantitative and qualitative analyses to deepen understanding. Finally, it provides recommendations into optimizing data analytics practices for fraud prevention and detection across GISA in ministries, institutions, and local government levels.

2. LITERATURE REVIEW AND HYPOTHESIS

Prevention and Detection of Fraud by Internal Auditors

Fraud prevention entails proactive actions like enforcing internal controls, segregation of duties, regular audits, and fostering an ethical culture through fraud awareness training (Bolton & Hand, 2002). Detection is enhanced through tools like data analytics, anomaly detection systems, and real-time monitoring, allowing auditors to identify unusual patterns promptly and improve response times to fraudulent activities.

Internal audits play a pivotal role in both fraud prevention and detection. According to IIA (2019), internal audits assess and reinforce organizational controls and governance by identifying risk areas, suggesting control improvements, and conducting fraud risk assessments. In detection, internal auditors use data analysis to identify red flags and take immediate investigative action, helping to reduce fraud's impact on organizations.

The ACFE Report to the Nations 2022 ranks internal audit as a leading fraud detection method globally and in Asia-Pacific, including Indonesia. To strengthen fraud resilience, Indonesian organizations can benefit from integrating advanced data analytics and real-time monitoring into their audit practices. These adjustments would align Indonesian internal audits with international standards, enabling a more proactive approach to fraud detection.

Research consistently shows the crucial role of internal audit in fraud prevention and detection. Studies by Abiola and Oyewole (2013), Crain et al. (2015), and Adekoya et al. (2023) emphasize the significant impact of internal audit on fraud detection. Abdullah (2014) underscores the value of internal audit in helping organizations manage risk and mitigate fraudulent activities. This aligns with Goodwin-Stewart and Kent's (2006) assertion that internal auditors provide vital support to management in areas like identifying business improvements, risk management, and addressing fraud.

Further studies reveal that internal audits enhance organizational controls and monitoring. Coram et al. (2008) found that internal audits add value through improved organisational controls and monitoring to detect fraudulent activities. Organizations with internal audits are more likely to detect fraud than those without internal audits. Ibrahim and Al-Haidari (2022) also found positive relationship between internal audit teams and corruption detection.

However, some studies indicate limitations in the effectiveness of internal audits. Mutambirwa et al. (2022) revealed that internal audit fails to address major forms of fraud like misuse of assets, cash theft, cheque tampering and payroll overstatement.

Role of Data Analytics in Fraud Prevention and Detection

Data analytics, rooted in disciplines like logic, mathematics, and computer science, offers valuable insights into identifying patterns and irregularities in organizational data. It is increasingly recognized for its ability to support fraud detection and risk management across sectors, with applications ranging from anomaly detection to real-time monitoring (Kaya et al., 2018). In internal audit, data analytics enables more accurate and efficient audits by quickly identifying anomalies within large datasets, thus enhancing audit effectiveness and allowing for timely interventions (Islam & Stafford, 2021; Jans et al., 2014).

Advanced data analytics tools, such as cluster analysis and machine learning models, facilitate pattern detection and anomaly identification, enabling auditors to proactively address fraud risks (Thiprungsri & Vasarhelyi, 2011). With the growth of big data analytics, internal audit functions have an opportunity to implement continuous, data-driven auditing practices, thus improving their ability to detect and mitigate fraud in real-time (Schneider et al., 2015). Thus, **Hypotheses 1–3** are:

There is a significant difference in internal audit effectiveness between GISA groups with high and low data analytics usage, across the full sample (H1), ministries/institutions (H2), and local governments (H3).

Data Analytics Usage and Internal Audit Effectiveness

The effectiveness of internal auditors in fraud detection is closely linked to their use of data analytics tools. Effective auditors tend to employ analytics as a core part of their methodology, a pattern supported by research from Novita and Anissa (2022) who suggest that organizations with a strong anti-fraud culture are more likely to invest in advanced data analytics for their auditors. Li et al. (2018) highlight that audit analytics software improves the ability to identify misstatements and fraud, especially when applied in high-risk areas, while Sipayung et al. (2023) emphasize that analytics skills among auditors contribute to improved judgment in fraud risk assessments.

A supportive organizational infrastructure also plays a role in facilitating effective fraud detection. For instance, organizations aligned with technological advancements tend to provide auditors with the necessary tools for comprehensive fraud risk analysis (Moradi & Nia, 2020; Rahayu et al., 2022). Thus, **Hypotheses 4–6** are:

There is a significant difference in data analytics usage between effective and ineffective GISA groups in fraud prevention and detection across the full sample (H4), ministries/institutions (H5), and local governments (H6).

Independence of Internal Auditors and Data Analytics Adoption

Internal audit independence is crucial to effective fraud detection. Independence allows auditors to carry out unbiased evaluations, free from external pressures (Nwaobia et al., 2021). Research shows that independent auditors, especially those equipped with data analytics, are better positioned to objectively assess and manage fraud risks (Onoja & Usman, 2015; Perols et al., 2016). Betti and Sarens (2020) add that independent auditors with analytics capabilities are more likely to adopt comprehensive, technology-driven approaches to fraud detection, facing fewer organizational barriers.

As data analytics tools evolve, independent auditors who use them can conduct more thorough assessments, leveraging insights that support proactive fraud detection and risk management. This link between internal audit independence, data analytics adoption, and fraud detection effectiveness underpins **Hypotheses 7–9**:

There is a significant difference in data analytics usage between independent and non-independent GISA groups in fraud prevention and detection across the full sample (H7), ministries/institutions (H8), and local governments (H9).

3. METHODS

Population and Sample

The population in this study consisted of all Ministries/Institutions and Local Governments Government Internal Supervisory Apparatus (GISA). Using purposive sampling, the sample was drawn specifically from auditors at the Team Leader (Auditor Muda) level across these entities. Team Leaders were selected because their roles encompass overseeing audit tasks, managing team activities, and preparing internal audit reports, providing a comprehensive view of internal audit functions. Data collection took place in 2022 and 2023, with 50 respondents meeting these criteria.

Data Collection

This study employs a sequential mixed-method design with an explanatory strategy, where quantitative data collected through a structured questionnaire were first analyzed, and the findings then guided the qualitative phase. Subsequent interviews with selected survey respondents provided insights to deepen and contextualize the quantitative results, offering a more comprehensive view of the initial survey findings.

Quantitative data were gathered through a structured questionnaire developed to assess three key dimensions central to GISA's approach in fraud prevention and detection: data analytics usage, internal audit effectiveness, and auditor independence. Each section was designed based on established literature, including those by Kamal & Elim (2021) and ACFE (2022), among others, to capture essential aspects of these areas. Appendix 1 summarizing the questionnaire's dimensions, questions, and supporting references.

Data Analytics Usage measures how frequently data analytics is used, with response options ranging from very often (4), quite often (3), sometimes (2), to rarely (1). Scores are grouped into high or low usage based on a cutoff of 3, reflecting broader engagement in data analytics. Internal Audit Effectiveness and Independence use yes/no responses across three questions, with scores of 2 or higher indicating "effective" or "independent" classifications, while scores below 2 denote otherwise.

To confirm the questionnaire's construct validity, a pilot test was conducted with auditors to ensure alignment with the study's constructs. Reliability was measured using Cronbach's Alpha, yielding values of 0.896 for data analytics, 0.872 for effectiveness, and 0.714 for independence, all meeting acceptable thresholds (>0.7), thereby affirming the consistency of responses across items.

Following the quantitative survey, 12 interviews were conducted with respondents selected based on their survey responses, representing varying levels of data analytics usage. This selection aimed to capture a range of perspectives on motivations, tool applications, and the perceived effectiveness of data analytics in fraud prevention and detection, thereby adding contextual depth to the quantitative findings.

The interviews focused on three main themes: frequency of data analytics usage, specific tools and applications in fraud detection, and overall effectiveness in fraud prevention. Appendix 2 summarizes these key themes, interview questions, and supporting references.

Data Analysis

This study employed a sequential mixed-methods approach, combining quantitative and qualitative analyses to gain a comprehensive understanding of data analytics practices within the Government Internal Supervisory Apparatus (GISA). The quantitative phase aimed to detect differences in data analytics usage across groups, while the qualitative phase provided insights into the motivations, tools, and perceived effectiveness driving these practices.

The quantitative analysis employed the Independent Samples T-test to compare mean differences in internal audit effectiveness based on data analytics usage, as well as mean differences in data analytics usage based on internal audit effectiveness and independence, as shown in Equations 1, 2, and 3 (Appendix 3). The analysis was conducted using Stata 16, with significance levels set at $p < 0.1$, $p < 0.05$, and $p < 0.01$, providing a robust framework for interpreting group differences relevant to GISA's audit practices.

Qualitative data analysis was conducted using thematic analysis of transcribed interview responses. Responses were coded and grouped into three primary themes: motivations for data analytics use, specific applications and tools, and perceived effectiveness. This thematic approach allowed for a structured exploration of factors influencing data analytics practices within GISA, including regulatory limitations, cost considerations, and skill gaps among auditors.

4. RESULTS AND DISCUSSION

Descriptive Analysis

Respondents in this study, comprising auditors from various ministries, institutions, and local governments (GISA and Local Government GISA), completed the questionnaire in 2022 and 2023, resulting in 50 valid responses. Table 1 presents a descriptive analysis of data analytics usage across key demographic categories.

In terms of gender, male respondents reported a higher average usage of data analytics (3.19) compared to females (2.27). This difference may reflect differences in roles, access to resources, or engagement with analytical tools in their respective positions.

Table 1. **Descriptive Statistics of Respondent Profile and Data Analytics Usage**

Profile	Category	N	%	Average Use of Data Analytics*
Gender	Male	30	60%	3.19
	Female	20	40%	2.27
Education Level	S1 (Bachelor's)	36	72%	2.75
	S2 (Master's)	14	28%	3.00
Age	≤ 35	15	30%	3.62
	36–45	27	54%	2.80
	> 45	8	16%	1.38
Years of Service	< 10 years	14	28%	3.62
	10–15 years	30	60%	2.76
	> 15 years	6	12%	1.28
Institution	Ministries/ Institutions	29	58%	2.93
	Local Government	21	42%	2.67

*mean score on a 4-point Likert scale from responses across three questions
Source: Processed Data

Examining education level, respondents with a Master's degree (S2) demonstrated a slightly higher average usage (3.00) than those with a Bachelor's degree (S1) at 2.75. This pattern aligns with the assumption that advanced education may equip auditors with stronger analytical skills or place them in roles requiring more data-driven approaches.

By age group, respondents aged 35 and below reported the highest average data analytics usage (3.62), followed by those aged 36–45 (2.80), with those over 45 showing the lowest average (1.38). This pattern could indicate generational differences in familiarity and comfort with data analytics, as younger respondents may have more recent exposure to relevant tools and technologies.

For years of service, respondents having less than 10 years reporting the highest average data analytics usage (3.62), while those with over 15 years reported the lowest (1.28). This trend may be due to recent hires receiving more training in data analytics, whereas long-tenured employees may lack the same level of exposure or necessity for analytics in earlier roles.

Lastly, across institution type, auditors in Ministries/Institutions had a higher average data analytics usage (2.93) compared to those in Local Governments (2.67). This may stem from differences in resource availability, institutional emphasis on data-driven decision-making, or training opportunities, with Ministries/Institutions potentially having more infrastructure to support data analytics.

T-Test Results

Internal Audit Effectiveness and Data Analytics Usage (Hypotheses 1–3)

Table 2, 3 and 4 illustrate the T-test results comparing internal audit effectiveness between GISA groups with high and low data analytics usage across the full sample, ministries/institutions, and local governments. For the full sample (Table 2), the high data analytics usage group has a mean internal audit effectiveness score of 2.71, significantly higher than the low usage group's score of 1.45 ($p = 0.0001$), supporting Hypothesis 1. This result indicates that higher data analytics usage corresponds with greater internal audit effectiveness, likely due to improved capabilities in fraud detection, pattern analysis, and comprehensive risk assessment.

In ministries/institutions (Table 3), the findings similarly support Hypothesis 2, with the high data analytics usage group reporting a mean internal audit

Table 2. **T-Test Results: Internal Audit Effectiveness in Fraud Prevention and Detection Based on Data Analytics Usage (Full Sample)**

	N	High DA Usage (H) Mean	N	Low DA Usage (L) Mean	Difference	Difference p-value
IA Effectiveness	28	2.7143	22	1.4545	1.2597	0.0001***
N	50					

$^{*}p < 0.1$, $^{**}p < .05$, $^{***}p < 0.01$

Source: Data Processed

Table 3. **T-Test Results: Internal Audit Effectiveness in Fraud Prevention and Detection Based on Data Analytics Usage (Ministries/Institutions Only)**

	N	High DA Usage (H) Mean	N	Low DA Usage (L) Mean	Difference	Difference p-value
IA Effectiveness	19	2.8421	10	1.1000	1.7421	0.0001***
N	29					

$^{*}p < 0.1$, $^{**}p < .05$, $^{***}p < 0.01$

Source: Data Processed

effectiveness score of 2.84 compared to 1.10 for the low data analytics usage group (p = 0.0001). This outcome highlights how ministries/institutions, benefiting from centralized resources, advanced infrastructure, and skilled personnel, are able to effectively leverage data analytics to enhance audit outcomes.

However, in the local government context (Table 4), the results do not support Hypothesis 3. Here, there is no statistically significant difference in internal audit effectiveness based on data analytics usage (p = 0.1267), with mean scores of 2.44 for high DA usage and 1.75 for low DA usage. This lack of significance may reflect resource and technological limitations within local governments, which constrain auditors' ability to fully utilize data analytics, regardless of their usage levels.

Data Analytics Usage Based on Internal Audit Effectiveness (Hypotheses 4–6)

Table 5, 6 and 7 illustrate T-test results comparing data analytics usage between effective and ineffective GISA groups for the full sample, ministries/institutions, and local governments. For the full sample (Table 5), Hypothesis 4 is supported, with effective groups showing a mean data analytics usage of 3.04 compared to 2.03 for ineffective groups (p = 0.0008). Similarly, Hypothesis 5 is supported for ministries/ institutions (Table 6), where effective groups report a mean usage of 3.29, significantly higher than the 1.81 reported by ineffective groups (p = 0.0001). In contrast, the result for Hypothesis 6 (Table 7) does not show a significant difference in local governments (p = 0.5102), with mean usage scores of 2.73 for effective groups and 2.42 for ineffective groups.

Table 4. **T-Test Results: Internal Audit Effectiveness in Fraud Prevention and Detection Based on Data Analytics Usage (Local Governments Only)**

	N	High DA Usage (H) Mean	N	Low DA Usage (L) Mean	Difference	Difference p-value
IA Effectiveness	9	2.4444	12	1.7500	0.6944	0.1267
N	21					

$^{*}p < 0.1$, $^{**}p < .05$, $^{***}p < 0.01$

Source: Data Processed

Table 5. **T-Test Results: Data Analytics Usage Based on Internal Audit Effectiveness in Fraud Prevention and Detection (Full Sample)**

	N	Effective (E) Mean	N	Ineffective (I) Mean	Difference	Difference p-value
Data_Analytics	39	3.0427	11	2.0303	1.0124	0.0008***
N	50					

$^{*}p < 0.1$, $^{**}p < .05$, $^{***}p < 0.01$

Source: Data Processed

Table 6. **T-Test Results: Data Analytics Usage Based on Internal Audit Effectiveness in Fraud Prevention and Detection (Ministries/Institutions Only)**

	N	Effective (E) Mean	N	Ineffective (I) Mean	Difference	Difference p-value
Data_Analytics	22	3.2879	7	1.8095	1.4784	0.0001***
N	29					

$^{*}p < 0.1$, $^{**}p < .05$, $^{***}p < 0.01$

Source: Data Processed

Table 7. **T-Test Results: Data Analytics Usage Based on Internal Audit Effectiveness in Fraud Prevention and Detection (Local Governments Only)**

	N	Effective (E) Mean	N	Ineffective (I) Mean	Difference	Difference p-value
Data_Analytics	17	2.7255	4	2.4167	0.3088	0.5102
N	21					

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Source : Data Processed

Table 8. **T-Test Results: Data Analytics Usage Based on Internal Audit Independence in Fraud Prevention and Detection (Full Sample)**

	N	Independent (I) mean	N	Non-Independent (NI) mean	Difference	Difference p-value
Data_Analytics	44	2.9015	6	2.2222	0.6793	0.0913*
N	50					

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Source : Data Processed

Table 9. **T-Test Results: Data Analytics Usage Based on Internal Audit Independence in Fraud Prevention and Detection (Ministries/Institutions Only)**

	N	Independent (I) mean	N	Non- Independent (NI) mean	Difference	Difference p-value
Data_Analytics	26	3.0385	3	2.0000	1.0385	0.0865*
N	29					

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Source : Data Processed

The significant results for Hypotheses 4 and 5 suggest that effective GISA groups likely prioritize data analytics to improve audit quality, adopting more data-driven, proactive approaches to fraud detection in ministries/institutions. Conversely, the non-significant result for Hypothesis 6 suggests that operational constraints in local governments may hinder the adoption of data analytics tools, regardless of audit effectiveness.

The non-significant result for Hypothesis 6 suggests that local governments' operational constraints-like limited budgets, staffing, and technology-may prevent effective GISA groups from fully utilizing data analytics. Unlike ministries/ institutions, local governments often deal with fragmented data infrastructure and restricted access to advanced tools, creating barriers to DA adoption. Differences in local policy priorities and resource allocations may further reduce the feasibility of adopting data-driven methods. These constraints highlight the need for targeted support and resources to enable local governments to make effective use of DA tools.

Internal Audit Independence and Data Analytics Usage (Hypotheses 7–9)

Table 8, 9, and 10 illustrate the T-test results for data analytics (DA) usage based on internal audit independence. For the full sample (Table 8), Hypothesis 7 is marginally supported, with independent groups showing a mean DA usage of 2.90 compared to 2.22 for non-independent groups (p = 0.0913). In ministries/ institutions (Hypothesis 8) as shown in Table 9, independent groups report a mean DA usage of 3.04, versus 2.00 for non-independent groups, also marginally significant (p = 0.0865). However, no significant difference in DA usage based on internal audit independence is found for local governments (Hypothesis 9) as shown in Table 10, with means of 2.74 and 2.22 for independent and non-independent groups, respectively (p = 0.3208).

These marginally significant findings for Hypotheses 7 and 8 suggest that internal audit independence in ministries/institutions may facilitate greater DA usage, enhancing internal auditors' decision-making autonomy and thoroughness. To strengthen DA application, ministries/institutions could implement policies that minimize managerial interference, fostering independent assessments backed by standardized DA tools and methods. This approach could further elevate audit quality through consistent, data-informed audits.

The lack of significant difference for local governments (Hypothesis 9) may indicate that even when GISA groups are independent, local governments face structural limitations, such as resource and technology shortages, that restrict the impact of independence on data analytics usage. Tailored resource allocation could help address these constraints, enabling local governments to enhance DA adoption regardless of internal audit independence.

Motivations for Data Analytics in Preventing and Detecting Fraud

GISA's use of data analytics in fraud prevention is limited due to a lack of regulatory requirements and high associated costs. GISA auditors highlighted:

> *"Because no regulations require us to use data analytics in fraud prevention and detection."*

> *"Because data analytics applications and training are quite expensive."*

Establishing a regulatory framework that encourages, or mandates data analytics could promote consistent use. GISA could also explore cost-effective solutions, like open-source software, and seek partnerships or grants to fund training.

GISA uses data analytics sporadically due to challenges in data access, unstructured data, and skill gaps among auditors:

> *"We sometimes have difficulty getting data... the data is often unstructured or unreliable."*

> *"Only certain people use data analytics... many auditors lack the necessary skills and training."*

Improving data governance to ensure structured, reliable data, along with expanding training programs focused on analytics skills, could address these barriers and empower auditors.

While data analytics helps expedite anomaly detection, manual methods are still used when data quality issues arise or for processes that remain unrecorded:

> *""Data analytics speeds up the discovery of anomalies"*

> *"Some aspects of fraud detection still require manual processes due to data integrity issues."*

Combining data analytics with manual audits where data quality is questionable could allow for a balanced approach that leverages both data-driven insights and traditional methods.

GISA frequently uses data analytics for efficient audits, enabling comprehensive fraud risk analysis by examining entire datasets:

Table 10. **T-Test Results: Data Analytics Usage Based on Internal Audit Independence in Fraud Prevention and Detection (Local Governments Only)**

	N	Independent (I) mean	N	Non-Independent (NI) mean	Difference	Difference p-value
Data_Analytics	18	2.7407	3	2.2222	0.5185	0.3208
N	21					

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Source: Data Processed

> *"Data analytics makes the process more efficient... analyzing large amounts of data and identifying anomalies."*

> *"Data analytics allows us to examine all data as a population... providing a more thorough fraud risk analysis."*

However, obstacles to optimal use-such as regulatory limitations, training deficits, and data access issues-irror findings by Lazarevska et al. (2022) and Banarescu (2015). Addressing these through regulatory support, cost-effective tools, improved data governance, and expanded training could significantly enhance GISA's capacity for effective data analytics in fraud prevention.

Data Analytics Applications/Tools in Preventing and Detecting Fraud

GISA relies primarily on Microsoft Excel and ACL for data analytics in fraud prevention, selecting tools based on data volume and task requirements. GISA auditors noted:

> *"Applications commonly used for data analytics by internal auditors are Microsoft Excel and ACL... Excel is easy and simple to use... If the data is very large, ACL is usually used, as it can be more optimal in finding data anomalies."*

> *"The ACL application... can find data anomalies, which are then investigated further to determine if fraud occurred?"*

While Excel and ACL are valued for their simplicity and functionality, they present limitations in handling large datasets and lack advanced analytical features. Excel struggles with scalability and lacks capabilities for data visualization and machine learning, restricting deeper, predictive analytics. ACL, while effective for moderate data volumes, requires specialized training and does not support complex predictive modeling or natural language processing (NLP), which could enhance fraud detection.

To address these limitations, other tools could offer GISA enhanced functionality. Programming languages like R and Python provide robust support for handling large datasets, with libraries for statistical analysis, machine learning, and data visualization. These tools enable advanced fraud detection techniques, including predictive analytics, which are essential for proactive fraud prevention. Visualization tools like Power BI and Tableau could also complement existing tools by providing interactive visualizations that help auditors identify trends and anomalies in large datasets.

GISA additionally employs SQL for data collection and Stata for specific fraud detection tasks, such as regression analysis to reassess budget allocations. GISA auditors commented:

> *"SQL is used to collect and process data... including detecting fraud or data anomalies."*

> *"Stata helps to identify potential fraud by re-performing budget allocation calculations and looking for anomalies."*

For unstructured data, GISA uses social media monitoring to profile employees and assess fraud risks:

> *"Unstructured data, such as information from social media, is used to profile employees... or conduct background checks on prospective vendors."*

Given the dynamic nature of fraud, incorporating AI-enhanced tools (e.g., NLP and machine learning) and diversifying beyond Excel, ACL, SQL, and Stata could significantly expand GISA's fraud detection capabilities. Studies, such as Bănărescu (2015), highlight that a broader range of analytical tools supports best practices in proactive fraud detection.

Data Analytics Effectiveness in Fraud Prevention and Detection

Data analytics significantly enhances GISA's ability to detect and prevent fraud by identifying suspicious patterns, enabling targeted supervision, and facilitating recalculations and anomaly detection in business processes. GISA auditors noted:

> *"Data analytics enables auditors to find suspicious transaction patterns... so supervision can be focused on these anomalies, making supervision more effective in preventing and detecting fraud."*

> *"Analytical data is also used to perform recalculations... helping to find anomalies in business transactions, which enhances supervision effectiveness."*

Data analytics also improves testing accuracy and objectivity, increasing the reliability of conclusions in fraud prevention:

> *"Data analytics can help the testing process be more accurate and objective, so conclusions are based on objective testing... making supervision more effective in preventing and detecting fraud."*

GISA further utilizes unstructured data analytics, like social media monitoring, to identify fraud risk indicators, such as extravagant lifestyles, which may signal potential red flags:

> *"Data analytics in the form of unstructured data... is used to monitor employee behavior and profile employees for red flags, like an overly luxurious lifestyle."*

Additionally, data analytics aids in assessing vendors for past legal issues and potential conflicts of interest with ministry employees:

> *"Data analytics is used to find information about providers... to detect any black records or relationships with ministry employees, which enhances fraud prevention."*

GISA auditors confirm the effectiveness of data analytics in fraud prevention:

> *"Using data analytics makes monitoring for fraud prevention and detection more effective than without data. So far, it has increased the effectiveness of fraud prevention and detection."*

5. CONCLUSION

This study explored the role of data analytics in enhancing fraud prevention and detection within internal audit practices across Indonesian government sectors, focusing on variations in data analytics usage, effectiveness, and independence within the Government's Internal Supervisory Apparatus (GISA). Results show that data analytics has the potential to significantly enhance fraud prevention and detection efforts within internal audit practices, especially within ministries/institutions.

Quantitative analysis supports Hypotheses 1, 2, 4, and 5, demonstrating a positive link between high data analytics usage and improved audit effectiveness. However, Hypotheses 3, 6, and 9, focused on local governments, did not yield significant results, highlighting potential resource and technology constraints in these contexts. These disparities emphasize the need for context-specific strategies, as data analytics usage and its effectiveness are influenced by organizational and resource-related factors.

Qualitative analysis reveals that GISA's primary motivations for data analytics use are to increase fraud prevention and detection (FPD) efficiency and broaden audit coverage. Common tools include Microsoft Excel and ACL, valued for ease of use despite limitations in handling large datasets and advanced analytics. Key barriers include regulatory gaps, high costs, data access issues, and skill shortages, underscoring the need for enhanced training and affordable analytics solutions to optimize GISA's capabilities.

Based on these findings, this study recommends establishing regulatory frameworks to standardize data analytics usage in fraud prevention and detection across government sectors. Ministries/institutions should consider increasing budget allocations for analytics tools and training, equipping auditors with the necessary skills and resources. For local governments, adopting cost-effective data analytics solutions and offering targeted training could help bridge current gaps in resources and skill sets, supporting autonomous, data-driven decision-making in fraud prevention. Policies that minimize management interference in audits could further support GISA's ability to operate independently and effectively.

This study has limitations. Self-reported data and interviews may introduce biases, affecting objectivity and generalizability. The local government sample may not fully capture regional challenges, limiting applicability. The tools assessed, like Excel and ACL, also lack advanced capabilities, potentially constraining auditors' capacity to detect complex fraud schemes. These limitations call for cautious interpretation and highlight the need for further research to validate and expand these findings.

Future research could explore how advanced data analytics technologies, such as machine learning and AI, impact audit effectiveness, given their potential to enhance anomaly detection and predictive capabilities. Investigating unstructured data analytics, like social media and text analysis, may also strengthen fraud prevention practices. Comparative studies across various government levels or regions would reveal specific challenges and opportunities in data analytics, fostering a deeper understanding of how technology can improve audit practices across diverse environments.

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Appendix 1. **Questionnaire Development and Theoretical Basis**

Questionnaire Section	Question	Explanation	References
Data Analytics Usage in Fraud Prevention and Detection	How often do internal auditors use data analytics in the audit process to detect fraud?	Measures the frequency of data analytics application, emphasizing proactive usage to detect fraud through data analysis tools.	Kamal & Elim (2021), Awuah et al. (2021), Alfian (2023)
	How often do internal auditors use data analytics to identify fraud risks in specific areas?	Assesses the use of data analytics for risk-based auditing in high-risk areas, aiding in early fraud risk identification.	Novita & Anissa (2022), Islam & Stafford (2021), Nugraha & Susanto (2017), Kamal & Elim (2021)
	How often do internal auditors use data analytics to monitor transaction patterns that could potentially indicate fraud?	Examines continuous monitoring practices in fraud detection, allowing for real-time anomaly detection in transaction patterns.	Aboud & Robinson (2020), Gupta (2019), Rosnidah et al. (2022)
Internal Audit Effectiveness	Did your internal audit successfully detect indications of fraud before any losses occurred?	Measures the proactive fraud detection capabilities of the internal audit function in preventing significant financial losses.	KPMG (2020), Suci et al. (2023), ACFE (2022)
	Were the measures taken after identifying fraud indications effective in preventing further issues?	Assesses the effectiveness of remedial actions, such as revising controls and enhancing training, to prevent future incidents.	PwC (2021), Indrawati et al. (2019), Widiyanti (2024)
	Was the internal audit able to respond and take action promptly when fraud was detected?	Evaluates the timeliness of responses, which is crucial in mitigating financial losses and restoring organizational integrity.	Deloitte (2022), Ridwan et al. (2021)
Internal Audit Independence	Does your internal audit have unrestricted access to all necessary information and data without any barriers?	Assesses whether auditors have adequate access to information, which is essential for thorough assessments (IIA, 2021).	IIA (2021), Syafitri et al. (2022), ACFE (2022)
	Is there external influence impacting auditors' decisions in detecting fraud?	Examines the independence of the audit function, focusing on minimizing external pressures for objective audits.	Deloitte (2022), Laming et al. (2019), Devi & Putra (2019)
	Does your internal audit have full autonomy to conduct audits without interference from others?	Assesses the audit function's autonomy, which is essential for unbiased and thorough assessments of fraud risks.	IIA (2021), Wilopo et al. (2018), Indrawati et al. (2019)

Source: Data Processed

Appendix 2. **Interview Questions and Theoretical Basis**

Interview Theme	Question	Explanation	References
Frequency of Data Analytics Usage in Fraud Prevention	Why does GISA very often/ quite often/sometimes/ rarely use data analytics in fraud prevention and detection?	Explores motivations, challenges, and factors influencing frequency of use, including regulatory requirements and costs.	Novita & Anissa (2022), Ovami & Muda (2023)
Applications and Tools in Fraud Detection	How is the use of various data analytics applications/ tools in preventing and detecting fraud by GISA?	Identifies specific tools like CAATs and their role in real-time monitoring and anomaly detection, exploring auditor choices and tool effectiveness.	Novita & Anissa (2022), Salijeni et al. (2021), Kukreja et al. (2020)
Effectiveness of Data Analytics in Fraud Prevention	How effective is data analytics in preventing and detecting fraud by GISA?	Examines the overall impact of data analytics on fraud prevention, linking effectiveness with enhanced accountability and risk assessment.	Sipayung et al. (2023), Al-Abedi (2023)

Source: Data Processed

Appendix 3. **Equations for Independent Samples T-Test**

Equation	Formula	Description
Equation 1	$t = \frac{\overline{IAE_H} - \overline{IAE_L}}{\sqrt{\frac{s_H{}^2}{n_H} + \frac{s_L{}^2}{n_L}}}$	Independent T-test to determine the average difference in Internal Audit Effectiveness (IAE) between GISA groups with high and low data analytics (DA) usage.
Equation 2	$t = \frac{\overline{DA_E} - \overline{DA_{NE}}}{\sqrt{\frac{s_E{}^2}{n_E} + \frac{s_{NE}{}^2}{n_{NE}}}}$	Independent T-test to determine the average difference in Data Analytics (DA) usage between effective and ineffective GISA groups for fraud prevention and detection.
Equation 3	$t = \frac{\overline{DA_I} - \overline{DA_{NI}}}{\sqrt{\frac{s_I{}^2}{n_I} + \frac{s_{NI}{}^2}{n_{NI}}}}$	Independent T-test to determine the average difference in DA usage between independent and non-independent GISA groups for fraud prevention and detection.

Notation	Definition
t	T-test statistic representing the difference between two GISA group means
$\overline{IAE_H}$	Average Internal Audit Effectiveness (IAE) score for GISA with high DA usage
$\overline{IAE_K}$	Average IAE score for GISA with low DA usage
$s_H{}^2$	Variance in IAE for GISA with high DA usage
$s_L{}^2$	Variance in IAE for GISA with low DA usage
n_H	Sample sizes for high DA usage GISA groups
n_L	Sample sizes for low DA usage GISA groups
$\overline{DA_E}$	Average Data Analytics (DA) usage for effective GISA
$\overline{DA_{NE}}$	Average DA usage for not effective GISA
$s_E{}^2$	Variance in DA usage for effective GISA
$s_{NE}{}^2$	Variance in DA usage for not effective GISA
n_E	Sample sizes for effective GISA groups
n_{NE}	Sample sizes for not effective GISA groups
$\overline{DA_I}$	Average DA usage for independent GISA
$\overline{DA_{NI}}$	Average DA usage for non-independent GISA
$s_I{}^2$	Variance in DA usage for independent GISA
$s_{NI}{}^2$	Variance in DA usage for non-independent GISA
n_I	Sample sizes for independent GISA groups
n_{NI}	Sample sizes for non-independent GISA groups

Source: Data Processed